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Research Paper

HYBRID ARTIFICIAL INTELLIGENCE METHODS FOR THE RELIABILITY ANALYSIS OF MULTI-STOREY FRAME STRUCTURES UNDER VARIOUS LOADING CONDITIONS

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Abstract - When civil engineering structures are exposed to unpredictable loading circumstances, structural reliability evaluation is crucial for assuring their safety and performance. When testing how structures react to different random variables, the traditional numerical methods that rely on running finite element simulations again and again are computationally intensive. A framework for dependability analysis of multi-storey frame structures exposed to variable lateral and combined loading conditions is proposed in this research, which is based on a mix of artificial intelligence techniques. Using SAP2000, numerical datasets were generated for a two-span, six-story plane frame structure that takes into account lateral stresses, gravity loads, and fluctuations in modulus of elasticity as unknown factors. By combining the results of the structure response data generation process with the optimization algorithms of the Random Forest (RF), Whale (WOA), and Sparrow Search (SSA), a hybrid machine learning model was created. In order to forecast the crucial node's lateral displacement under various loading situations, the models that were constructed were trained and evaluated.

Utilizing statistical indicators such as Nash-Sutcliffe efficiency (NS), adjusted R^2, performance index (PI), variance account factor (VAF), Legate and McCabe index (LMI), Willmott index (WI), root mean square error (RMSE), mean absolute error (MAE), weighted mean absolute percentage error (WMAPE), and scatter index (SI), the suggested models' performance was assessed. In addition, the models' reliability performance was evaluated using the FOSM approach, which measures the reliability index (H) and the probability of failure (Pf). According to the findings, each of the suggested hybrid models managed to get a remarkable level of prediction accuracy. The RF-WOA model showed better reliability performance and generalizability for structures that were loaded floor-wise laterally. During the testing and training stages, RF-DOA obtained the best prediction accuracy when subjected to a combination of gravity and lateral loads. The results of the reliability study show that hybrid AI models are a good substitute for computationally heavy structural evaluation methods and can accurately forecast the reaction of structures.

Important Terms -Various terms such as structural reliability, machine learning, artificial intelligence, random forest, multi-story frame, reliability index, and probability of failure are used.

I. INTRODUCTION

As the need for efficient, cost-effective, and environmentally friendly structural systems continues to grow, contemporary civil engineers are more focused on ensuring the safety and dependability of these systems. Uncertainties in structural response may be introduced into multi-story frame buildings due to the numerous loading situations that these structures are typically exposed to, such as gravity loads, wind loads, and seismic forces. Variations in loading situations, geometric factors, environmental impacts, and material qualities all contribute to these errors. For this reason, trustworthy structural design relies on precise failure probability assessments and predictions of structural behavior. In order to assess a structure, traditional deterministic structural analysis techniques often use predetermined safety factors and design specifications. The probabilistic character of structural uncertainty may be underrepresented by these approaches, despite their widespread use in engineering practice. By taking structural resistance and applied demand changes into account, reliability-based analysis offers a more reasonable approach. An essential way to measure structural safety levels and assess the chances of reaching an undesired limit state is using the reliability index (β) and probability of failure (Pf).

It is common practice to run many numerical simulations using finite element analysis tools in order to evaluate the reliability of complicated structural systems. Conventional numerical procedures are computationally costly and time-consuming when dealing with several unknown factors. A viable solution to these restrictions for predicting structural reactions with less computing effort has been the emergence of surrogate models based on artificial intelligence (AI). Without the need for explicit analytical formulations, machine learning algorithms may discover intricate nonlinear correlations between input variables and structure responses. Predicting material characteristics, estimating structural responses, detecting damage, and assessing dependability are just a few of the many machine learning applications that have grown in recent years within structural engineering. Random Forest (RF) is one of several machine learning algorithms that has recently come under scrutiny for its impressive predictive power, resilience against overfitting, and capacity to deal with nonlinear connections. Traditional machine learning models rely heavily on optimizing their parameters for optimal performance. Results show that hybrid approaches, which integrate optimization methods with machine learning algorithms, are more accurate and dependable.

To enhance predictive performance, machine learning models have been effectively combined with metaheuristic optimization methods that are based on natural processes. Highly developed swarm intelligence methods for optimizing model parameters include the Dragonfly Optimization Algorithm (DOA), the Whale Optimization Algorithm (WOA), and the Sparrow Search Algorithm (SSA). When applied to complicated structural issues, these optimization techniques may provide hybrid RF models with better generalizability and forecast accuracy. This research looks at the dependability of a two-span, six-story plane frame building under various loads. In order to account for changes in modulus of elasticity, combined gravity and lateral loading, and variations in lateral loading, a numerical database was created using SAP2000. Three RF-DOA, RF-WOA, and RF-SSA hybrid AI models were created using the produced datasets. The reliability of the projected structural displacements was assessed using the First Order Second Moment (FOSM) approach, and a number of statistical indicators were used for this purpose. The following are the primary aims of this study:

- In order to forecast the displacement response of multi-story frame structures subjected to unknown loading circumstances, it is necessary to create hybrid AI models.
- The goal is to use statistical performance indicators to assess how well the RF-DOA, RF-WOA, and RF-SSA models work.
- In order to evaluate hybrid models' predictive power in two different loading scenarios: floor-wise lateral loading and combined loading.
- In order to calculate the dependability index and failure probability by using structural reactions anticipated by AI.
- In order to find the best hybrid AI model for structural evaluation based on dependability.

Faster and more accurate assessment of structural performance under unknown loading circumstances is made possible by the suggested technique, which offers an effective framework for merging reliability analysis with artificial intelligence. By using this method, structural engineers may create designs that are less prone to errors and more dependable without having to rely as much on computationally heavy numerical simulations.

II. SURVEY OF LITERATURE

Many studies have looked at structural reliability analysis as a way to assess the security and efficiency of engineering systems in the face of uncertainty. There has been extensive use of traditional reliability techniques for failure probability estimation, including the First Order Reliability Method (FORM), Second Order Reliability Method (SORM), First Order Second Moment (FOSM), and Monte Carlo Simulation (MCS). Cornell (1969) presented a probabilistic approach to structural safety by factoring in the unknowns of structural resistance and applied stresses. One of the foundational methodologies in structural reliability evaluation was proposed by Hasofer and Lind (1974)—an invariant reliability index—furthermore improving reliability analysis. A variety of building components, such as frameworks, bases, retaining walls, and composites, have been subjected to reliability assessments of structural systems. By studying the dependability of frame structures with brittle components, Bennett (1985) shown that structural safety evaluations need probabilistic evaluations. In his research on structural reliability issues, Dolinski (1982) found that first-order second-moment approximation was useful for calculating failure probability with little computing effort. The moment-based approaches for structural reliability analysis were reviewed in detail by Zhao and Ono (2001), who also addressed their uses in engineering systems.

Recent years have seen a surge in interest in structural engineering applications of artificial intelligence and machine learning methods, thanks to developments in computational methodologies. Machine learning models may learn complicated correlations between input parameters and structural responses, making them effective alternatives to traditional numerical simulations. The Random Forest technique was created by Breiman (2001). It uses a combination of decision trees to decrease overfitting and increase prediction accuracy. Numerous structural prediction and reliability-related challenges have made use of Random Forest's resilience and capacity to describe nonlinear behavior. Artificial intelligence algorithms have been shown to be useful in structural reliability analysis, according to research. When comparing neural network-based response surface models for structural reliability evaluation to traditional methods, Beheshti Nezhad et al. (2019) found that the former were more computationally efficient. The capacity of machine learning models to decrease processing needs was proved by Wang et al. (2020), who studied machine learning-assisted static structural reliability analysis for functionally graded frame structures. Implementing soft computing methods into geotechnical engineering reliability analyses, Ray et al. (2021) demonstrated the efficacy of AI-based methods in capturing intricate nonlinear interactions. Predictions about structures are now much more accurate and dependable thanks to hybrid machine learning models. To optimize model parameters and enhance prediction performance, optimization methods that draw inspiration from natural systems have been merged with machine learning models. Based on the swarming behavior of dragonflies, Mirjalili (2016) developed the Dragonfly Algorithm (DOA), which has been effectively used to solve optimization challenges. The Whale Optimization Algorithm (WOA), developed by Mirjalili and Lewis (2016), is a powerful search tool for resolving difficult optimization issues. Taking cues from sparrow behavior, Xue and Shen (2020) created the Sparrow Search Algorithm (SSA), an optimization method for swarm intelligence that has great potential for exploration and exploitation.

Reliability assessment using hybrid AI techniques has grown more popular in structural engineering. When analyzing the dependability of gravity retaining walls, Mustafa et al. (2022) used hybrid ANFIS models and showed that their prediction performance was better. The efficacy of AI-based approaches for probabilistic evaluation was validated by Ray et al. (2023), who studied the reliability study of reinforced soil slopes using hybrid soft computing techniques. In their evaluation of machine learning-based approaches in structural reliability analysis, Saraygord Afshari et al. (2022) emphasized the increasing significance of AI techniques for future applications in reliability-based design. Machine learning models were shown to be capable of predicting structural displacement and reliability characteristics in an investigation of frame structures subjected to top-floor lateral loads by Sufyan et al. (2023). The feasibility of artificial intelligence (AI) surrogate models for assessing structural safety was validated in a separate research by Sufyan et al. (2024), which used machine learning techniques to examine portal frame dependability under different lateral loads. Hybrid optimization-based Random Forest models for multi-storey frame structures under diverse loading situations have received less attention in structural reliability analysis, despite the fact that prior studies have shown the usefulness of machine learning approaches in this area. For that reason, this research creates and assesses RF-DOA, RF-WOA, and RF-SSA models to forecast the reaction to displacement and the dependability performance of multi-story frame buildings that experience floor-wise lateral loading and combined loading.

III. STUDY DESIGN

This study's technique includes producing uncertain input-output information, developing hybrid AI models, predicting structural displacement, and evaluating dependability. It also includes numerical modeling of a multi-storey frame structure. The four main parts of the study framework are as follows: (1) creating structural models and datasets, (2) building hybrid machine learning models, (3) evaluating the prediction models' performance, and (4) doing reliability analysis utilizing the FOSM method.

A. Generating Structural Models and Datasets

The current study made use of a two-span, six-story plane frame building. A numerical model was created to assess the structural response to various loading situations using the SAP2000 finite element program. Beam and column members of the frame have fixed cross-sectional characteristics, but the modulus of elasticity is a material property that is unpredictable. The range of Young's modulus (E) that was deemed appropriate was 2.0 × 10^8 kN/m² to 1.8 × 10^8 kN/m². A critical node at the frame's top level was used to measure the structural reaction in terms of horizontal displacement. The displacement values that were created using SAP2000 were used as the target output values for the development of AI models. The study took into account two distinct loading scenarios:

1) Condition for Lateral Loading on Floors

Each level of the multi-story frame was subjected to its own set of lateral stresses in the first instance. Along with the modulus of elasticity, various combinations of lateral forces were taken into account as input variables. The SAP2000 analysis yielded the appropriate horizontal displacement response.

2) Concurrent Loading Situation

In the second scenario, the frame experienced both vertical and horizontal loads. Both the structural parts' own weight and any live loads applied to beam components made up the gravity load. In addition to different lateral loads and modulus of elasticity, a total gravity load of 21.31 kN/m was taken into account. The displacement numbers that came out of it were calculated using numerical methods. One hundred samples were produced at random for each of the two loading conditions. The structural displacement values and input parameters were stored in separate datasets. In order to prepare the produced datasets for the creation of machine learning models, they were standardized.

B. Building AI Models with Hybrid Features

By combining optimization methods with Random Forest (RF), three hybrid ML models were created:

- Application of the Dragonfly Optimization Algorithm to Random Forests (RF-DOA)
- Application of the Whale Optimization Algorithm to Random Forests (RF-WOA)
- Optimizing Random Forest with the Sparrow Search Algorithm (RF-SSA)

The Random Forest technique is a kind of ensemble learning that uses a combination of decision trees to decrease variance and increase prediction accuracy. Incorporating optimization methods improved the standard RF model's prediction capabilities by identifying optimum model parameters. A training dataset and a testing dataset were created from the normalized dataset in a proportion of 70:30. The hybrid AI models were trained on the training dataset and then tested on the testing dataset to assess how well they generalized to new data. The variables that were inputted were:

- Partial loads (P) on the sides
- Weight factors for gravity loading (w), if relevant
- Elastic modulus (E)

What came out of it was:

- Distortion of structural elements

The purpose of training the created models was to determine nonlinear correlations between displacement response and unknown structural characteristics.

C. Criteria for Evaluating Performance

A number of statistical measures were used to assess the created AI models' prediction performance. These metrics quantify how well the projected displacement values using AI match up with the real SAP2000 findings. Various performance metrics were taken into account:

- Efficiency coefficient of the Nash-Sutcliffe model (NS)
- R^3 indicates the coefficient of determination.
- Adjusted determination coefficient (Adj.R^2)
- Index for performance (PI)
- Factor for variance accounting (VAF)
- The LMI, built by Legate and McCabe,
- Index of Willmott Agreement (WI)
- The RMSE is the root-mean-square error.
- Standard deviation (SD)
- Mean absolute percentage error weighted
- Scattered index

A model was deemed to have better prediction capabilities if it had greater values of NS, R^3, Adj.R^2, PI, VAF, LMI, and WI, and lower values of RMSE, MAE, WMAPE, and SI.

D. Analyzing Reliability with the FOSM Method

First Order Second Moment (FOSM) analysis was used to determine the dependability. By factoring in unknowns related to structural capacity and demand, reliability analysis determines a structure's degree of safety. By definition, the performance function is:

$$m(X) = C - D$$

when it comes to: Structure capacity or permitted displacement is denoted by C. D is the expected demand for structural elements. When the performance function is positive, it means everything is OK, and when it's negative, it means something went wrong.

The reliability index was calculated as:

$$\beta = \frac{\mu_m}{\sigma_m}$$

or

$$\beta = \frac{\mu_C - \mu_D}{\sqrt{\sigma_C^2 + \sigma_D^2}}$$

The performance function's standard deviation (σm), mean value (μm), and the average values of capacity (μC) and demand (μD) are all aspects to consider. The standard deviations of capacity and demand are represented by ωC and σD, respectively. In order to determine the likelihood of failure, we used:

$$P_f = 1 - \Phi(\beta)$$

where the ordinary normal cumulative distribution function is denoted by Ŧ(ŗ). The structural reliability performance is better when the reliability index (β) is greater and the probability of failure (Pf) is lower.

IV.FINAL THOUGHTS AND ANALYSIS

Predicting the displacement response of the multi-storey frame structure under various loading circumstances was done using the created hybrid artificial intelligence models. Their performance was assessed. Statistical performance indicators and reliability analysis were used to evaluate the three models that were developed: RF-DOA, RF-WOA, and RF-SSA. Each floor-wise lateral loading condition and combined loading condition were compared independently.

A. Forecast Accuracy in Floor-Wise Lateral Stress Conditions

The RF-DOA, RF-WOA, and RF-SSA models' predictive capabilities were assessed with the use of training and testing datasets derived from SAP2000 analysis. All three hybrid models showed remarkable accuracy in their predictions, according to the statistical performance measures. While training, RF-SSA outperformed the other models by a little margin, reaching the maximum values for NS, R^3, Adj.R^3, LMI, PI, and VAF. A high level of agreement between the predicted and actual displacement values was shown by the model's R^2 value of 0.99956 and NS value of 0.99978. There was almost no difference in the prediction accuracy between RF-DOA and RF-WOA, and both showed similar performance. In terms of prediction capabilities during testing, RF-WOA outperformed the other two models. With NS = 0.99879, R^2 = 0.99758, Adj.R^2 = 0.99741, PI = 1.99583, and VAF = 99.88035%, the model was successful. Additionally, RF-WOA demonstrated its better capacity to generalize to unknown datasets by obtaining the lowest scatter index (SI = 0.00862) and weighted mean absolute percentage error (WMAPE = 0.00623). While RF-SSA did somewhat better in training, it did slightly worse in testing when compared to RF-WOA. Throughout all stages, RF-DOA maintained performance levels somewhere in the middle of RF-SSA and RF-WOA. According to the findings, optimization procedures greatly enhanced the Random Forest model's prediction capabilities, with the most dependable prediction being provided by RF-WOA when subjected to floor-wise lateral stress.

B. Performance of Predictions Under Conditions of Combined Loading

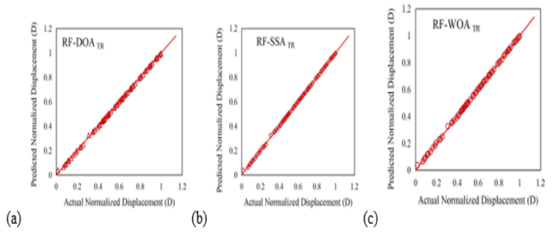
Additional testing was conducted on the created hybrid models with both gravity and lateral loads applied simultaneously. As a consequence of successfully capturing complicated nonlinear interactions between structural factors and displacement response, all models were shown to have achieved good prediction accuracy. Among the models tested, RF-DOA produced the most accurate predictions during training, with NS and R^2 values of 0.99956. In comparison to RF-SSA and RF-WOA, the model achieved the lowest RMSE (0.00018), MAE (0.00010), and WMAPE (0.00190), all of which indicate the smallest prediction error. The results of the tests likewise showed that RF-DOA was the best option. The model yielded the following results: NS = 0.99861, R^2 = 0.99861, Adj.R^2 = 0.99850, VAF = 99.86074%, and WMAPE = 0.00515. Although their accuracy ratings were somewhat reduced, RF-WOA and RF-SSA both continued to exhibit outstanding predictive capabilities. The findings show that when coupled loading circumstances are present, RF-DOA performs better in forecasting displacement. The enhanced searching ability of the Random Forest model is a direct result of the effective parameter optimization capabilities of the Dragonfly Optimization Algorithm, which is responsible for the increased performance.

C. Methods for Evaluating Prediction Models

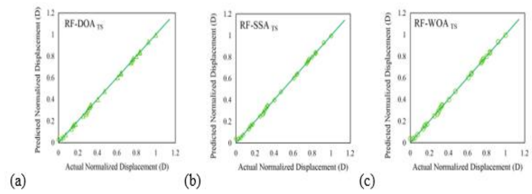
We used ranking analysis using all statistical performance metrics to find the top-performing model overall. The model that performed the best for each indicator was given Rank 1, while the models that performed worse were given higher rankings. To get the total rating of performance, all the individual rankings were added together. Among the three models, RF-WOA performed the worst when it came to floor-wise lateral loads. Despite RF-SSA's superior performance in training, RF-WOA outperformed the competition in testing and ultimately took first place. When it came to mixed loading circumstances, RF-DOA came out on the bottom. Confirming its strong prediction capabilities under complicated loading circumstances, the model obtained Rank 1 in all performance measures for both the training and testing datasets. According to the findings of the ranking, the loading scenario determines the optimal hybrid model. When considering both gravity and lateral loads simultaneously, RF-DOA improves prediction accuracy, while RF-WOA is more suited to dealing with variable lateral loads delivered at various floor levels.

D. Linear Regression

We used regression analysis to look at how the hybrid AI models' projected values compared to the real SAP2000 displacement values. By graphically displaying how near the expected values are to the perfect 1:1 agreement line, regression curves provide a visual picture of prediction accuracy.



See Figure 1. for a comparison of the two training sets for normalized displacement: (a) RF-DOA and (b) RF-SSA. "RF-WOA" (c)



As shown in Figure 2, the following testing sets compare actual and anticipated normalized displacement: (a) RF-DOA, (b) RF-SSA, and (c) RF-WOA.

Actual and anticipated displacement values for floor-wise lateral loads were highly correlated across all three models. A tight distribution of projected points around the ideal regression line proved that the models were successful. During testing, RF-WOA had the best agreement with real values out of the three models.

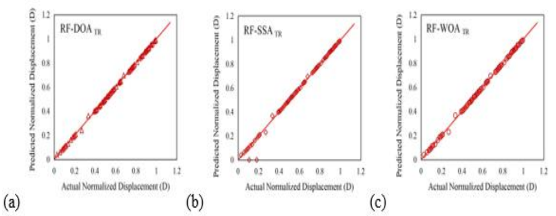
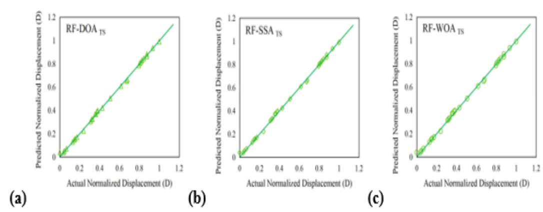


Figure 3: (a) RF-DOA and (b) RF-SSA, training sets for actual and predicted normalized displacement, respectively (c) WOA-RF



As shown in Figure 4, the following testing sets compare actual and anticipated normalized displacement: (a) RF-DOA, (b) RF-SSA, and (c) RF-WOA.

The best match between predicted and actual displacement values was seen under combined loading circumstances using RF-DOA. According to the statistical findings, RF-DOA successfully captured the nonlinear connection between loading factors, material qualities, and structural displacement response, as shown by the regression behavior.

E. Analyzing Reliability with the FOSM Method

The created models were tested for dependability using the First Order Second Moment (FOSM) method. We compared the dependability values (β) and failure probability (Pf) that were predicted using AI with the actual values that were generated from SAP2000. With a failure probability of 3.91×10^{-6}, the actual dependability index for floor-wise lateral loading was found to be β = 4.47017. The RF-DOA, RF-SSA, and RF-WOA dependability indices that were predicted were highly congruent with the real value. Out of the three models, RF-WOA produced the most reliable results with the best reliability index (β = 4.49129) and the lowest failure probability (Pf = 3.54×10^{-6}).

Model	Actual β	Actual Pf	Model's β	Model's Pf	Rank
RF-DOA	4.47017	3.91E-06	4.49010	3.56E-06	2
RF-SSA	4.47017	3.91E-06	4.48937	3.57E-06	3
RF-WOA	4.47017	3.91E-06	4.49129	3.54E-06	1

Evaluation of the reliability index (γ) - lateral forces on every level (Table 1)

The dependability index β = 5.46914 with a significance level of Pf = 2.26×10^{-8} was determined under combined loading circumstances. Following closely after were RF-SSA and RF-DOA, with RF-WOA achieving the greatest anticipated reliability index (β = 5.50128) and the lowest likelihood of failure (Pf = 1.8853×10^{-8}). In terms of accuracy for predicting displacement, RF-WOA was somewhat better than RF-DOA, although both methods were reliable.

Model	Actual β	Actual Pf	Model's β	Model's Pf	Rank
RF-DOA	5.46914	2.26E-08	5.49976	1.9015E-08	3
RF-SSA	5.46914	2.26E-08	5.50116	1.8865E-08	2
RF-WOA	5.46914	2.26E-08	5.50128	1.8853E-08	1

Table 2. Assessment of the Reliability Index (β) - total pressures on every level

In sum, the results of the reliability study show that hybrid AI models successfully mimic the features of multi-story frame structures when it comes to dependability. These models are effective substitutes for numerical reliability assessments since AI-based reliability values are so close to numerical reliability values.

V. CONCLUSION

A framework for reliability analysis of multi-storey frame structures exposed to varied loading circumstances was described in this research. The framework is hybrid and based on artificial intelligence. Through the use of SAP2000, numerical datasets were produced for a two-span, six-story planar frame that took uncertainties in lateral loading, gravity loading, and modulus of elasticity into account. Three hybrid machine learning models—RF-DOA, RF-WOA, and RF-SSA—were trained and tested using the produced datasets to forecast structural displacement and evaluate reliability performance. In the face of unknown loading circumstances, the constructed hybrid AI models proved to be very adept in predicting structural displacement. As evidence of their efficacy as surrogate modeling methodologies, all three models produced answers that were in good agreement with the real SAP2000 findings. While RF-WOA demonstrated improved prediction capabilities in the testing phase, RF-SSA demonstrated marginally better performance in the training phase under floor-wise lateral stress circumstances. After comparing the three models using ranking analysis, RF-WOA emerged as the clear winner, demonstrating its superior capacity to generalize to structural response data that has never been seen before.

We found that RF-DOA achieved the best prediction accuracy in training and testing when subjected to a combination of gravity and lateral loads. Its appropriateness for complicated loading situations was shown by the model's lowest prediction errors and maximum statistical performance values. All of the constructed models showed a high degree of agreement between the actual and anticipated displacement values, according to the regression analysis. The suggested hybrid AI framework was proven accurate as the projected replies were tightly clustered around the optimal agreement line. Results from reliability testing utilizing the First Order Second Moment (FOSM) technique demonstrated that the AI models' predictions of failure rates and reliability indices were very close to the real numerical outcomes. RF-WOA demonstrated exceptional reliability estimation capabilities, as it attained the greatest reliability index and the lowest failure probability under both loading circumstances.

While retaining excellent prediction accuracy, the research shows that hybrid AI models may drastically cut down on computing effort needed for repeated finite element simulations. These models provide a dependable and effective method for assessing the performance of structures and for designing with dependability in mind. More complicated structural systems may be included into the suggested AI-based dependability framework by adding uncertainties such environmental degradation, geometric changes, material deterioration, and seismic impacts. The results show that Random Forest models based on hybrid optimization are useful for analyzing the dependability of multi-story frame constructions. In the presence of mixed loading, RF-WOA improves the capacity of reliability prediction and RF-DOA delivers better accuracy in displacement prediction. Building safer, more cost-effective, and more robust structural systems is a potential goal of integrating AI with reliability analysis.

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